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Estimating the Effectiveness of a Vehicle Miles Traveled Tax In Reducing Particulate Matter (PM2.5) Emissions

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ABSTRACT

This study estimates the effectiveness of a vehicle miles traveled (VMT) tax in controlling mobile-source emissions of particulate matter ($PM_{2.5}$) in a non-attainment area located in northern Utah. Using a recently updated household-level dataset, we find no evidence of an endogenous relationship between choice of vehicle type and VMT. We also estimate VMT elasticities with respect to cost per mile that are in some cases larger in magnitude than those reported in previous studies. Based on vehicle emissions tests performed by the Houston Advanced Research Center, we estimate the reduction in $PM_{2.5}$ emissions that would occur with two different sets of VMT tax rates. Principle findings are that a VMT tax rate of \$0.003 per passenger car mile and \$0.01 per light-duty truck mile (resulting in a mean annual tax burden of \$128 per household in the first year) would reduce annual $PM_{2.5}$ emissions by between 7% and 11%, depending upon the degree of heterogeneity in household driving behavior. At tax rates of \$0.006 and \$0.02 per mile for passenger cars and light-duty trucks, respectively (resulting in double the mean annual tax burden), annual $PM_{2.5}$ emissions would be reduced by between 12% and 23%. Both the advantages and limitations of the VMT tax are discussed.

JEL Classification:
Keywords: Vehicle miles traveled (VMT) tax; VMT elasticity; Particulate Matter ($PM_{2.5}$)
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Estimating the Effectiveness of a Vehicle Miles Traveled Tax In Reducing Particulate Matter ($PM_{2.5}$) Emissions[†]

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December 20, 2006

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In Reducing Particulate Matter ($PM_{2.5}$) Emissions

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1. Introduction

The United States Environmental Protection Agency (EPA) sets the National Ambient Air Quality Standards (NAAQS) as benchmarks for identifying non-attainment areas nationwide – regions with measured concentrations above the NAAQS for at least one of six criteria air pollutants. The standards are adjusted periodically based on new evidence concerning the pollutants' effects on human health and the environment. For example, the particulate matter ($PM_{2.5}$) maximum-allowable 24-hour standard has recently (as of September 27, 2006) been reduced from $65\mu g/m^3$ to $35\mu g/m^3$, based in part on results from health-risk studies such as Ostro, Broadwin, and Green (2006) and Pope et al. (1995).[1] As the NAAQS are adjusted over time, state and local governments must consider implementing new policies that protect public health and maintain (or re-attain) attainment status. Implementing new policies is especially challenging in the case of $PM_{2.5}$ emissions since the primary sources of these emissions are mobile. This paper assesses the potential of one such policy – a tax on vehicle miles traveled (VMT).

A number of previous studies have found the elasticity of VMT with respect to cost per mile (henceforth VMT elasticity) to be inelastic, which suggests that a VMT tax would have to be set prohibitively high in order to reduce emissions enough to maintain attainment status.[2] Our results suggest otherwise in certain cases. Using recently updated household-level survey data for the Mountain West region, we find that VMT is generally elastic with respect to cost per mile under the assumption of homogeneous households and that VMT elasticity for passenger cars varies in an interesting way across households

[1] Ostro, Broadwin, and Green (2006) find that an increase in $PM_{2.5}$ by 10 $\mu g/m^3$ corresponds to a 0.6% increase in risk of mortality.
[2] For example, see Walls, et al. (1993), Sevigny (1998), and West (2004). We compare our elasticity estimates with the estimates from these studies in Section 4.

with one, two, and three or more vehicles. In particular, we find that VMT elasticity *decreases* for passenger cars as we move from one-vehicle to three-or-more vehicle households.[3] This suggests that the scale effect for households owning more than one passenger car outweighs the countervailing cross-vehicle substitution effect. By "scale effect" we mean the extent to which a multi-vehicle household is predisposed toward (or requires) vehicle travel, as reflected in its decision to own more than one passenger car. By "substitution effect" we mean the degree to which the multi-vehicle household substitutes VMT across passenger cars as the cost per mile changes

Under the assumption of heterogeneous households we find that VMT elasticities are generally inelastic for vehicles that are used primarily for commuting purposes, but again elastic for non-commuting vehicles. We also find that VMT elasticity increases in magnitude as household income level decreases for two- and three-or-more vehicle households.

We use our elasticity estimates to assess the effectiveness of different VMT tax rates in reducing $PM_{2.5}$ emissions in a non-attainment area located in northern Utah. Our principle findings are that a VMT tax rate of \$0.003 per passenger car mile and \$0.01 per light-duty truck mile (resulting in a mean annual tax burden of \$128 per household in the first year) would reduce annual $PM_{2.5}$ emissions in our study area by between 7% and 11%. At tax rates of \$0.006 and \$0.02 per mile for passenger cars and light-duty trucks, respectively (resulting in double the mean annual tax burden), annual $PM_{2.5}$ emissions would be reduced by between 12% and 23%. To our knowledge, this is the first attempt

[3] However, VMT elasticity generally increases for light-duty trucks as we move from one- to three-or-more vehicle households.

at empirically estimating the regional effect of a VMT tax in reducing mobile-source $PM_{2.5}$ emissions.

Two strands of the taxation literature set a context for the VMT tax. First is the literature addressing output (e.g., VMT) versus emissions (e.g., $PM_{2.5}$) taxes. Fullerton, et al. (1999) use a simple general equilibrium framework to show that the welfare gain from output taxes is approximately half the gain from emissions taxes. However, Schmutzler and Goulder (1997) demonstrate that emissions taxes are generally suboptimal in the presence of monitoring costs. By contrast, output taxes are optimal under sufficiently high monitoring costs, sufficiently limited options for emission reduction other than through output reduction, and sufficiently high substitutability of output (for multi-product firms). In both studies, output and emissions are assumed to be products of stationary sources – for good reason. Direct taxation of mobile-source emissions is known to be both technologically and politically impractical (Fullerton and West, 2002).

Second is the input-tax literature (e.g., a gas tax or a subsidy based on a specific vehicle attribute). Previous studies have mostly argued against the use of a gas tax to control mobile-source emissions. For instance, Devarajan and Eskeland (1996) and Sevigny (1998) cite the weak correlation between fuel efficiency and emissions as the main drawback of a uniform gas tax. Innes (1996) points out that siphoning from low- to high-emissions vehicles is likely a major monitoring problem with a gas tax. Also, a gas tax may cause households to drive fewer miles using their old gas-guzzlers and *more* miles using their newer fuel-efficient cars. By comparison, the main monitoring problem with a VMT tax is the potential roll-back of odometers.

There are two additional problems that gas and VMT taxes share when it comes to controlling localized pollution such as $PM_{2.5}$ emissions. First is the problem of seasonality. In this paper's study area – Cache County, Utah – $PM_{2.5}$ emissions pose a threat to public health primarily during the winter inversion season (from the months of November through March).[4] Second, not all of a typical household's annual VMT occurs strictly within Cache County. To be efficient, gas and VMT taxes must therefore be levied solely during the winter inversion months and applied strictly to VMT occurring within the local area of concern. Unfortunately, the only way to levy such a discriminatory VMT tax is via statistical averaging using more disaggregated household-level survey data than is currently available. In particular, monthly (as opposed to annual) VMT would need to be reported, along with information on the proportion of a vehicle's VMT occurring within the county. Average sample proportions (categorized, say, by some attribute of vehicle type) could then be applied to the household's annual VMT (per vehicle) to determine its adjusted annualized VMT tax.[5,6]

Issues of seasonality and location aside, Fullerton and West (2000) provide a numerical analysis of a uniform gas tax, both alone and in tandem with subsidies for engine size and vehicle age. They find that the combination of a gas tax and subsidies achieves approximately 70 percent of the welfare gain associated with a Pigovian tax on emissions, while a gas tax alone achieves slightly over 60 percent of the welfare gain.

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[4] Cache County borders the state of Idaho. Approximately 100,000 people reside in the county, with the largest concentration (40%) in the city of Logan.

[5] Although it could potentially be levied seasonally, a gas tax cannot be applied strictly to locally occurring VMT, even with statistical averaging. An additional disadvantage with a gas tax is the inability of the taxing authorities to prevent drivers from purchasing their gas in neighboring counties (although Cache County is large enough such that this might not be problem in the larger metropolitan areas). A gas tax does, however, provide control for pollution caused from idling engines, whereas a VMT tax does not.

[6] The need to adjust the VMT tax for seasonality and location suggests that the efficient VMT tax is some proportion (either less than or greater than one) of the estimated annualized VMT tax for Cache County households derived below in Section 5.

The authors also find that the tax/subsidy rates are set too low when household-specific and vehicle-specific heterogeneity is ignored.[7] Fullerton and West (2000) conclude that the relative effectiveness of the gas tax in reducing emissions is due to its impact on VMT. This, in turn, demonstrates the fundamental appeal of a VMT tax – it is applied directly to the main source of the emissions problem.[8]

The next section presents a simple description of how households choose VMT per vehicle and how corresponding VMT elasticities are derived. A full model of the household decision process is contained in a technical appendix (Appendix 1).[9] Section 3 describes the data used to estimate VMT elasticity and provides descriptive statistics. Section 4 discusses the methodology used to estimate VMT elasticity and presents our empirical results. Section 5 turns to estimating the potential impact of a VMT tax on $PM_{2.5}$ emissions. Section 6 summarizes and concludes.

2. VMT Elasticity

Let household *i*'s utility function be expressed as $U^i = U^i(z_i, \boldsymbol{m}_i, E, \boldsymbol{\Omega}_i)$, where z_i is a numeraire good, m_{ij} is VMT per vehicle type *j* ($m_{ij} \geq 0$ $i = 1,..., n$, $j = 1,.., m$), and $\boldsymbol{m}_i$ $= \{m_{ij}\}_j$ represents household *i*'s vector of m_{ij} (for vehicle types not owned by household *i* m_{ij} equals zero, otherwise, $m_{ij} > 0$ reflects the sum of all mileage driven on vehicles of

---

[7] Fullerton and West (2000) consider heterogeneity with respect to vehicle-based functions (i.e., the shape of the emissions-per-mile and miles-per-gallon functions) and household behavior (i.e., the correlation between VMT and vehicle attributes). The former type of heterogeneity is what we refer to as vehicle specific and the latter type is referred to as household specific. Since VMT varies by household, a VMT tax is by its very nature household specific.

[8] In a related paper, Fullerton and West (2002) consider three alternative first-best tax scenarios (in comparison with an emissions tax) – a vehicle-specific gas tax; a vehicle-specific tax based on attributes such as engine size, pollution control equipment (PCE), and VMT; and a three-part taz/subsidy on gas, engine size, and PCE. They find that in order for a first-best gas tax to be feasible, the attributes of each vehicle would have to be identifiable at the pump.

[9] Appendix 1 is available online at www.econ.usu.edu/acaplan/VMTappendix1.pdf.

type j owned by household i). Further, $e_{ij} = f^j(m_{ij})$ is (uniformly-mixed) emissions based on VMT per vehicle type j, where $e_{ij} \geq 0$, $f^j(0) = 0$, and $f_m^j > 0$.[10] Total emissions generated by all households is represented by $E = e_i + E_{-i}$, where $e_i = \sum_j e_{ij}$ is total emissions generated by household i from its fleet of vehicles and $E_{-i} = \sum_{-i} \sum_j e_{-ij}$ is total emissions from all vehicles type j driven by all other households $-i$. $\boldsymbol{\Omega_i}$ is a vector of demographic characteristics, such as household size and composition, location (urban vs. rural), etc. Lastly, U^i is increasing and quasi-concave in z_i and $\boldsymbol{m_i}$, and decreasing and concave in E.

Household i's budget constraint is expressed as $y_i = z_i + \boldsymbol{P_j(\theta_j)m_i}$, where y_i represents income level and $\boldsymbol{P_j(\theta_j)}$ is a vector of non-environmental variable costs per mile for vehicle type j based on a corresponding vector of cost-related attributes $\boldsymbol{\theta_j}$. Included in $\boldsymbol{\theta_j}$ are vehicle maintenance and fuel expenses. Henceforth, we write $\boldsymbol{P_j(\theta_j)}$ as $\boldsymbol{P_j}$ for notational simplicity. Appendix 1 shows that household i's problem results in the Kuhn-Tucker conditions

$$m_{ij}\left[\frac{U^i_{m_j}}{U^i_z} + \frac{f^j_m U^i_E}{U^i_z} - P_j\right] = 0,\ i = 1,....,n,\ j = 1,....,m \qquad (1)$$

which, *inter alia*, defines the household's VMT demand $m_{ij} \equiv m_{ij}(\boldsymbol{P_j}, y_i, E_{-i}, \boldsymbol{\Omega_i})$ from vehicle j, $j = 1,...,m$. The first term in the square brackets of (1) is the household's willingness to pay (WTP) for VMT from vehicle j, while the second term represents the

[10] Superscripts on functions identify household i or vehicle type j, while subscripts represent partial derivatives with respect to the identified variable. For expository purposes we assume function f is deterministic. In reality, this function is subject to uncertainty with respect to technological and environmental factors.

household's WTP for reducing (its own) emissions from vehicle j. We note that VMT demand from vehicle j can be expressed conveniently in elasticity form,

$$\varepsilon_{m_{ij}} = \frac{\partial m_{ij}}{\partial P_j} \frac{P_j}{m_{ij}} \tag{2}$$

where in practice m_{ij} is evaluated at a mean value across all households i. This elasticity measures the percentage change in VMT from vehicle type j by household i with respect to a 1% increase in variable cost per mile.

The set of household- and vehicle-specific first-best VMT tax rates is derived in Appendix 1. We demonstrate in Section 5 how a general VMT tax can be combined with an estimate of $\varepsilon_{m_{ij}}$ from (2) to estimate an associated reduction in emissions.

3. Data and Descriptive Statistics

Our data for estimating (2) is taken from the Mountain census district of the 2001 Regional Transportation and Energy Consumption Survey (RTECS), made available from the Energy Information Administration (EIA) of the U.S. Department of Energy. The 2001 RTECS is the most recent household-level transportation survey conducted in the U.S.[11] It is a clustered survey containing a wide range of information on over 22,000 different households driving approximately 43,000 different vehicles across nine census districts. To represent conditions in Cache County, Utah we restrict the data to the Mountain census district, which covers our study area (see Figure 1). The Mountain sample includes approximately 1600 households, corresponding to just over 3100 different vehicles.

[11] The 2001 RTECS data updates the dataset used by Sevigny (1998).

As mentioned in Section 1, Cache County is plagued by mobile-source $PM_{2.5}$ emissions, which pose a significant threat to public health during the winter inversion months. Though population density is moderately low, topographic and meteorological conditions in the county magnify the impact that mobile sources have on ambient air quality. Figure 2 shows the periods over the past five years during which $PM_{2.5}$ concentration levels in the county have risen above the old and new NAAQS of 65 $\mu g/m^3$ and 35 $\mu g/m^3$, respectively. The county has experienced 102 hazard days above the new standard and 29 hazard days above the old standard.

Table 1 presents descriptive statistics for, and brief descriptions of, the basic variables used in our empirical analyses (the household subscript *i* has been dropped for convenience).[12] "First vehicle" denotes the vehicle identified by the household as its primary source of transportation; "second vehicle" denotes its secondary source of transportation, etc. The variable *hhcomp* is an index variable indicating household composition. The value of this variable increases as the overall age distribution of the household increases, e.g., a household where the age of the oldest child is less than seven years gets a "1", a household where the age of the oldest child is between seven and 15 years gets a "2", up to "10" for a two-adult household with no children where the age of the household head is no less than 60 years.[13] The $avecost_j$, j = 1,2,3 variable is based on detailed records kept by the household throughout the year. Lastly, $truck_j$, j = 1,2,3 indicates vehicle type. The other vehicle types are passenger car, van, and SUV.[14]

[12] Various interaction terms, formed from combinations of these variables, are described when presented in Section 4.

[13] Full descriptions of this and all other variables used in the analysis of Section 4 are available upon request from the authors.

[14] We also estimated the regression models discussed in Section 4 with the dummy variables car_j , j = 1,2,3, where car_j = 1 if the vehicle is passenger car and 0 otherwise. We also used miles-per-gallon to proxy for vehicle type. The results using these vehicle-type measures were qualitatively similar to those using $truck_j$.

To determine how representative the Mountain sample is of our study area, we compare in Table 2 the sample mean values for *income*, *gender*, *urban*, and $truck_j$ with corresponding population values for Cache County using data available from the Utah Department of Motor Vehicles (DMV, 2006), Utah Highway Performance Monitoring System (2006), and U.S. Census Bureau (2000). From Table 2, we note that average household income, percentage of middle-income households, percentage of males, and percentage of households owning a light-duty truck are higher in Cache County, and that percentage of lower-income households and percentage of households located in an urban area are lower than in the Mountain sample. Also, there are fewer one-vehicle but more two- and three-vehicle households in Cache County than in the sample.

4. Empirical Estimates of VMT Elasticity

Train (1986), Walls et al. (1993), and Sevigny (1998) have shown that households with different vehicle arrangements will likely respond differently to a VMT tax. In particular, households owning one-, two-, and three-or-more vehicles have different substitution possibilities in their respective consumption bundles, suggesting that households be grouped accordingly. We therefore estimate separate VMT elasticities that capture behavioral differences across households owning different numbers of vehicles.

In addition, there are two types of simultaneity that might preclude us from relying strictly on an ordinary least squares (OLS) specification for estimating VMT. The first type pertains to a household's joint decision of which types of vehicles to purchase and how many miles to drive using each type. This is the endogeneity issue raised by West (2004). A second type of simultaneity arises for multi-vehicle households, where estimating VMT necessitates joint estimation of VMT demand equations that are related by way of possible VMT substitutions across vehicles.

To address these simultaneity issues, we stratify our dataset into sub-samples of households owning one-, two-, and three-vehicles and independently test each vehicle's VMT in each sub-sample for the first type of simultaneity using a standard Hausmann (1978) test. We control for the possible existence of the second type of simultaneity in multi-vehicle households through the use of Seemingly Unrelated Regression (SUR) analysis (Zellner, 1962).

Lastly, we estimate VMT under the assumptions of 'homogeneous' and 'heterogeneous' households. The empirical model for heterogeneous households includes a series of interaction terms that adjust the VMT elasticity estimates based on income category (i.e., *lowinc* and *midinc*) and whether a vehicle is used for commuting purposes (i.e., cm_j). The model for homogeneous households does not include these interaction terms. Estimating both homogeneous and heterogeneous models enables us to derive a range of possible outcomes for the different tax scenarios presented in Section 5. We begin our discussion of the estimation procedures and attendant empirical results using the sub-sample of one-vehicle households.[15]

<u>One-Vehicle Households</u>

Following Sevigny (1998), we assume OLS specifications of VMT for homogeneous and heterogeneous households, respectively,

$$\begin{aligned} lvmt_1 = \alpha_0 + \alpha_1(lincome) + \alpha_2(lavecost_1) + \alpha_3(numdrive) + \alpha_4(hhcomp) \\ + \alpha_5(cm_1) + \alpha_6(urban) + \alpha_7(truck_1) + \alpha_8(intert_1) + \alpha_9(gender) + \mu_1 \end{aligned} \tag{3a}$$

[15] Nlogit version 3.0.10 was used to generate the following results.

$$
\begin{aligned}
lvmt_1 = {} & \beta_0 + \beta_1(lincome) + \beta_2(lavecost_1) + \beta_3(numdrive) + \beta_4(hhcomp) \\
& + \beta_5(cm_1) + \beta_6(urban) + \beta_7(truck_1) + \beta_8(intert_1) + \beta_9(gender) \\
& + \beta_{10}(intercm_1) + \beta_{11}(interlinc) + \beta_{12}(interminc) + \eta_1
\end{aligned} \tag{3b}
$$

where $lvmt_l$, $lincome_l$, and $lavecost_l$, respectively, are the logarithms of vmt_l, $income_l$, and $avecost_l$; $interact_l$ is an interaction term equal to the product of $lavecost_l$ and $truck_l$; the α's and β's are coefficients to be estimated; and μ_l and η_l are potentially a non-spherical error terms due to the possible endogeneity of $truck_l$.[16] Coefficients α_1 and β_1 provide estimates of household income elasticity of VMT demand, α_2 and β_2 estimates of VMT elasticity ($\varepsilon_{m_{ij}}$), α_3, α_4, β_3, and β_4 estimates of household-size and household-composition effects, α_5 and β_5 commuter car effects, α_6 and β_6 urban-rural location effects, α_7 and β_7 vehicle-type effects, α_8 and β_8 adjust the estimates of $\varepsilon_{m_{ij}}$ for vehicle type (the term $intert_l$ equals $truck_l \cdot lavecost_l$), and α_9 and β_9 control for gender of head of household. Coefficients β_{10}, β_{11}, and β_{12} further adjust the estimate of $\varepsilon_{m_{ij}}$ for whether the vehicle is used for commuting purposes and the household's income status, respectively ($intercm_1 = cm_1 \cdot lavecost_l$, $interlinc_1 = lowinc \cdot lavecost_l$, and $interminc_1 = midinc \cdot lavecost_l$).

Following Hausmann (1968), we test for the endogeneity of $truck_l$ in (3a) and (3b) by including the residuals, res_l, from (3a) and (3b) as an explanatory variables in the probit equations,

$$
prob(truck_1 = 1) = \frac{e^{\gamma X}}{1 + e^{\gamma X}} + \upsilon_1 \tag{4}
$$

[16] A null hypothesis for a test of the endogeneity of $truck_l$ can therefore be expressed as μ_l being a mean-zero, normally distributed error term.

where $\boldsymbol{X}$ is a subset of explanatory variables from Table 1 (including res_1), γ is a corresponding vector of coefficients, and υ_1 is a mean-zero normally distributed error term. Estimation results for (4) are contained in a technical appendix (Table A2-1 of Appendix 2).[17] Most importantly for our purposes, the statistical insignificance of the coefficient for res_1 indicates that $truck_1$ can be treated as an exogenous explanatory variable in (3a) and (3b).

The exogeneity of $truck_1$ in our sample is not particularly surprising, as there is no a priori reason to presume that households choosing to drive more miles than average are necessarily more likely to choose light-duty trucks or passenger cars based, say, on fuel-efficiency comparisons. Other concerns, such as safety and comfort, may be as important to households as fuel efficiency. Thus, on average the direction of endogeneity between vehicle type and VMT may not be empirically discernable – two households that are the same in every other respect may choose different vehicle types due to latent heterogeneity. Or it may simply be that on average, concerns for safety, comfort, and fuel efficiency offset each other. For these reasons, we find that endogeneity of vehicle type does not exist for the average household in our sample.

Table 3 contains our VMT estimation results for the sub-sample of one-vehicle households. As expected, the coefficient estimates for *lincome*, *numdrive*, and cm_1 are positive in both specifications, indicating that higher-income households with more drivers who use the household's vehicle primarily for commuting purposes tend to drive more miles per year, all else equal. Households with fewer young children (e.g., a larger

[17] Appendix 2 is available online at www.econ.usu.edu/acaplan/VMTappendix2.pdf. We provide results based on equation (3a) (as well as equations (5a) and (6a) to follow), as the results for (3b) (and (5b) and (6b) to follow) are (respectively) qualitatively similar. The results for (3b), (5b), and (6b) are available upon request from the authors.

hhcomp value) drive fewer miles on average. Vehicle type and household location (urban vs. rural) have no discernable effects on VMT.

Most importantly for our purposes, the coefficient estimates for $lavecost_1$ in both specifications are negative and statistically significant, indicating that on average, VMT elasticity for one-vehicle households is negative (and elastic). Further, the coefficient estimates from (3b) for $lavecost_1$ and $intercm_1$ indicate that households using their vehicle for commuting purposes exhibit a significantly lower VMT elasticity than households that do not. This makes intuitive sense, since households that depend on their vehicle for commuting to work may have (or perceive themselves as having) fewer transportation alternatives for most of the VMT put on the vehicle. Lastly, the statistical significance of the F-statistics (at the 1% level) indicate that the coefficients in the respective models are jointly different than zero.

These results differ from West's (2004) in some important respects. For instance, West finds a significant positive effect for her measure of *urban* and a significant negative effect for her measure of *numdrive*. Her average VMT elasticity estimate of -0.93 is also generally lower than ours, which equals -1.85 in specification (3a) and -2.34 for non-commuters and -0.66 for commuters in specification (3b). Also, West's estimate of VMT income elasticity of 0.02 is similarly lower than ours, which equals 0.17 in specification (3a) and 0.13 in specification (3b).

<u>Two-Vehicle Households</u>

Similar to the approach used for the sub-sample of one-vehicle households, we begin with specifications of VMT for homogeneous and heterogeneous households for each of two vehicles, respectively

$$
\begin{aligned}
lvmt_j = \alpha_{0j} &+ \alpha_{1j}(lincome) + \alpha_{2j}(lavecost_1) + \alpha_{3j}(lavecost_2) + \alpha_{4j}(numdrive) \\
&+ \alpha_{5j}(hhcomp) + \alpha_{6j}(cm_j) + \alpha_{7j}(urban) + \alpha_{8j}(truck_j) \\
&+ \alpha_{9j}(intert_j) + \alpha_{10j}(gender) + \mu_{2j}, \ \ j = 1,2
\end{aligned} \tag{5a}
$$

$$
\begin{aligned}
lvmt_j = \beta_{0j} &+ \beta_{1j}(lincome) + \beta_{2j}(lavecost_1) + \beta_{3j}(lavecost_2) + \beta_{4j}(numdrive) \\
&+ \beta_{5j}(hhcomp) + \beta_{6j}(cm_j) + \beta_{7j}(urban) + \beta_{8j}(truck_j) \\
&+ \beta_{9j}(intert_j) + \beta_{10j}(gender_j) + \beta_{11j}(intercm_j) \\
&+ \beta_{12j}(interlinc_j) + \beta_{13j}(derminc_j) + \mu_{2j}, \ \ j = 1,2
\end{aligned} \tag{5b}
$$

where subscript j refers to the first and second vehicle, respectively. The interpretations of the α and β parameters, the explanatory variables, and the error term, μ_{2j}, are the same as for the one-vehicle households.[18]

Again following Hausmann (1968), we test for the endogeneity of $truck_j$ by including the residuals, res_j, $j = 1,2$, from separate estimations of (5a) and (5b) as explanatory variables in corresponding probit regression equations (4).[19] Estimation results for each vehicle using (4) are presented in Tables A2-2 and A2-3 of Appendix 2. Most importantly for our purposes, the statistical insignificance of the coefficients for res_j indicate that $truck_j$, $j = 1,2,$ respectively, can be treated as exogenous explanatory variables in (5a) and (5b).

To account for fact that equations (5a) and (5b) represent respective systems of VMT demand equations, we use the SUR estimation method to estimate VMT for each of the two vehicles, and apply homogeneity and Walrasian demand restrictions to enhance the efficiency of the estimates (Mas-Colell, et al, 1995; Greene, 2003). Our SUR results,

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[18]Note that $intercm_j = cm_j \cdot lavecost_j$, $interlinc_j = lowinc \cdot lavecost_j$, $interminc_j = midinc \cdot lavecost_j$, and $intert_j = truck_j \cdot lavecost_j$, j=1,2. The inclusion of $lavecost_2$ in (5a) and $lavecost_1$ in (5b) controls for cross-price effects.

[19] In this case (4) can be written as $prob(truck_j = 1) = \dfrac{e^{\gamma_j X_j}}{1 + e^{\gamma_j X_j}} + \upsilon_{2j}$, j = 1,2.

along with results for equation-by-equation OLS estimation of vehicle-specific VMT, are presented in Tables 4a and 4b. In the following discussion we compare the OLS results for equation (3b) in Table 3 with the SUR results for equations (5b) in Table (4b).[20]

Similar to the one-vehicle households, the income elasticity of demand for VMT and the commuter-car dummy variable are both positively related to VMT – for each vehicle, respectively, in the two-vehicle households. The respective income elasticities are noticeably higher for two-vehicle households, suggesting that VMT is income elastic for these households. The coefficient estimates for *numdrive*, *hhcomp*, and *gender* are no longer statistically significant. However, $truck_2$ now takes on a negative sign, indicating that, all else equal, if the second vehicle of a two-vehicle household is a truck the household chooses to drive that vehicle fewer miles.

Both vehicles in the two-vehicle household exhibit negative VMT elasticities, which are both smaller in magnitude than the estimated elasticity for one-vehicle households.[21] The VMT elasticity for the first vehicle is -1.16 if the household is high income (larger than $62,500 per year) and the vehicle is not used for commuting purposes. Comparable estimates for middle- and lower-income households are -1.37 and -1.44, respectively, indicating that these two-vehicle households are, all else equal, more responsive to changes in per-mile fuel costs of the first vehicle. If instead the first vehicle is used for commuting purposes, the VMT elasticity estimates drop considerably, to -0.31, -0.52, and -0.59 for high-, middle, and lower-income households, respectively.

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[20] The statistical significance of the Wald Chi-Square statistic (at the 1% level) indicates that the SUR restrictions of homogeneity and Walrasian demand yield more efficient coefficient estimates.

[21] Thus the scale effect outweighs the substitution effect, as discussed in Section 1. Note that this occurs solely for passenger cars (and light-duty trucks if they are the household's first vehicle), as the coefficient estimate for $intert_2$ adds a "base" of -0.91 to the non-commuter VMT elasticity for each income category.

The *relative* VMT elasticity estimates for the second vehicle are similar. If the vehicle is not used for commuting purposes, the elasticity estimates are -1.10, -1.29, and -1.38 for high-, middle-, and lower-income households, respectively. If instead the second vehicle is used for commuting, the corresponding estimates are 0.33, 0.14, and 0.05. Theoretically speaking, a positive elasticity suggests an upward-sloping VMT demand for this type of household, which is unappealing. In an empirical sense, however, the positive signs suggest that households of this type which face higher per-mile fuel costs also happen to commute more miles. In other words, it could be that these households commute further distances because of some latent fixed effect, not because their fuel costs are higher.[22]

Three-or-More Vehicle Households

Our homogeneous and heterogeneous specifications for estimating VMT for each of three vehicles is the same as (5a) and (5b), respectively, except that $lavecost_3$ and *vehgrt3* are included as additional explanatory variables in both equations and $j = 1,2,3$. We henceforth label these augmented equations (6a) and (6b). Again the interpretations of the α and β parameters, the explanatory variables, and the error term, μ_{3j}, are the same as for the one- and two-vehicle households. Results for the equation-by-equation endogeneity tests of $truck_j$ using res_j, $j = 1,2,3$, based on separate estimations of (6a), are included in Appendix 2. The results show that $truck_j$ can be treated as exogenous explanatory variables in (6a) and (6b).

We again use the SUR estimation method to estimate (6a) and (6b) as respective systems of VMT demand equations. Our SUR and equation-by-equation OLS results for

[22] We also estimated (5b) without the cm_j and $truck_j$ variables included. In this case, the coefficient estimate for $intercm_j$ became negative, suggesting that households which use their second vehicle for commuting purposes have higher VMT elasticities.

three-or-more vehicle households are presented in Tables 5a (homogeneous households) and 5b (heterogeneous households). Comparing heterogeneous two- and three-vehicle households (Tables 4b and 5b), we find similar results for income elasticity (generally income elastic), VMT elasticity (larger for lower- and middle-income households and the truck dummy for secondary vehicles, but lower for commuter vehicles), the commuter dummies, and the truck dummy for secondary vehicles. Also, VMT elasticities are positive for second and third vehicles that are used for commuting purposes. Unlike for two-vehicle households, *hhcomp* is negatively related to VMT for three-vehicle households.

VMT elasticity estimates for the one-, two-, and three-or-more vehicle households are compiled in Table 6, along with comparable estimates from previous studies. One cross-study comparison worthy of note is that our estimates based on the homogeneous household model (which are more directly comparable to the previous studies' estimates) are larger – in some instances we find that VMT is highly elastic with respect to fuel costs per mile. One reason for this difference could be that households, on average, have become more responsive to increases in fuel costs over time.[23] Another reason could be differences in the sample data themselves. Recall that our data is an updated version of the dataset used in Sevigny (1998), and the sample frame is restricted to the Mountain district. The main advantage of our dataset is that $avecost_j$ is reported directly by the household – for each vehicle – based on its own records kept during the year. The main disadvantage of our dataset is that $truck_j$ is a highly aggregated attribute upon which to base vehicle type.

[23] Recall that our data covers households in 2001, while the previous studies' results are based on household samples conducted in the mid-1990s and earlier.

Although it contains information on several different, and more disaggregated, vehicle attributes, West's (2004) dataset suffers from two potential deficiencies.[24] First, West's *avecost*$_j$ variable is constructed by dividing the price per gallon of gasoline by fuel efficiency of the vehicle type reported by the household. Actual variable costs per mile are therefore not reported directly by the household. Second, the data contains total gas expenditure per household, not per vehicle. Thus, the data cannot account for possible substitution effects across vehicles for a given household, which may in turn bias household VMT estimates downward.

5. Estimating the Impacts of a VMT Tax on $PM_{2.5}$ Emissions

Using our VMT elasticity estimates from Table 6, we are able to assess the effectiveness of different VMT tax rates in reducing $PM_{2.5}$ emissions in Cache County, Utah. To begin this component of the analysis, we estimate baseline $PM_{2.5}$ emissions in Cache County by applying to the Mountain sample vehicle emissions tests reported in Yu and Qiao (2004) for light-duty trucks and passenger cars. In specific, we assume 67.57 g/mi and 20.76 g/mi (all roads) $PM_{2.5}$ emission rates for light-duty trucks and passenger cars, respectively (where g/mi stands for grams per mile).[25] As a result of combining this information, we obtain estimates of aggregate $PM_{2.5}$ emissions for light-duty trucks and passenger cars in the Mountain sample based on actual VMTs reported for each vehicle in the sample. We then extrapolate these aggregate emission estimates to Cache County's population of vehicles (most recently reported by Utah DMV, 2006) by applying to the Mountain sample estimates the ratio of Cache County light-duty trucks and passenger cars.

[24] West's (2004) dataset is compiled from the 1997 Consumer Expenditure Survey and the California Air Resources Board Surveillance Program.

[25] Yu and Qiao (2004) do not report separate emissions results for vans and SUVs. Since light-duty trucks, vans, and SUVs generally match in terms of vehicle weight, engine size, and fuel burn we lump vans and SUVs with light-duty trucks rather than with passenger cars for this analysis.

For example, in the Mountain sample there are a total of 1,318 light-duty trucks (as defined for this analysis) with an aggregate annual VMT of 16.1 million, resulting in an estimated aggregate $PM_{2.5}$ emissions from light-duty trucks of 1.1 million kilograms (kg) per year (0.06757 kg/mi x 16.1 million mi/yr = 1.1 million kg/yr). By comparison, the Cache County fleet consists of 23,055 light-duty trucks. Therefore, our estimate of aggregate $PM_{2.5}$ emissions in Cache County attributable to light-duty trucks is 19.1 million kilograms per year (1.1 million kg/yr x (23,055/1,318) = 19.1 million kg/yr). An equivalent approach results in a baseline estimate of 10.5 million kilograms per year of aggregate $PM_{2.5}$ emissions attributable to passenger cars in Cache County. Thus, our baseline estimate of aggregate $PM_{2.5}$ emissions for Cache County is 29.6 million kilograms per year.[26]

Next, we use the VMT elasticity estimates obtained from this study to derive associated estimates of VMT reductions attributable to tax-induced increases in $avecost_j$. These VMT reductions are calculated as follows. For each vehicle in our sample, we initially assume a vehicle-specific VMT tax rate t_j, $j = 1,2$, for passenger cars and light-duty trucks (where passenger cars and trucks are distinguished according to the $truck_j$ variable – see Table 1) and determine each vehicle's new VMT, labeled VMT'_{ij}, according to,

$$VMT'_{ij} = VMT_{ij}\left[1 + \frac{t_j \varepsilon_{m_{ij}}}{avecost_{ij}}\right],\ i = 1,\ldots,n,\ j = 1,2 \tag{7}$$

[26] A simpler approach would have been to multiply the product of Yu and Qiao's (2004) $PM_{2.5}$ emissions estimates and Utah DMV's (2006) estimate of average VMT for trucks and passenger cars by the total number of light-duty trucks and passenger cars, respectively, in the Cache County fleet. However, this approach seems less precise because only an average VMT is used rather than actual VMTs reported by households themselves in a survey. Ideally, the Utah Department of Environmental Quality would calculate an annual estimate of $PM_{2.5}$ emissions (and perhaps concentrations themselves) attributable to mobile sources in Cache County. To our knowledge though, such estimates do not currently exist.

where VMT_{ij} represents initial, or current vehicle-specific VMT, and the term $t_j \varepsilon_{m_{ij}} / avecost_{ij} < 0$ is the percentage change in VMT in response to t_j, $j = 1,2$ (using our empirical estimates of $\varepsilon_{m_{ij}}$ derived in Section 4). We calculate (7) for each household twice – once using the VMT elasticity estimates obtained under the homogeneous-household assumption and again under the heterogeneous household assumption.

Next, identically to how we calculated $PM_{2.5}$ emissions above, we calculate new vehicle-specific emissions by multiplying VMT'_{ij} by our per mile emission rates of 67.57 g/mi and 20.76 g/mi for light-duty trucks and passenger cars, respectively. Lastly, we calculate the percentage change in $PM_{2.5}$ emissions ($\Delta PM_{2.5}$) as,

$$\Delta PM_{2.5} = \frac{\sum_i \sum_j \left[VMT_{ij} \cdot PM_{2.5}^{ij} \right] - \sum_i \sum_j \left[VMT'_{ij} \cdot PM_{2.5}^{ij} \right]}{\sum_i \sum_j \left[VMT_{ij} \cdot PM_{2.5}^{ij} \right]} \cdot 100 \tag{8}$$

where $PM_{2.5}^{ij}$, $j = 1,2$, represents the per mile emission rates for passenger cars and light-duty trucks, respectively.

Results using (8) are presented in Table 7 for two different tax scenarios. In the first scenario, we assume relatively moderate per-mile tax rates of \$0.003 and \$0.01 for passenger cars and trucks, respectively.[27] In the second scenario, we double these tax rates to \$0.006 and \$0.02 per mile, respectively. As indicated in Table 7, under the assumption of homogeneous households aggregate $PM_{2.5}$ emissions decrease by 11% under the first tax scenario and by 23% under the second, with corresponding average annual tax burdens for the first year of \$128 and \$256. We again emphasize that these estimated annual emissions reductions and associated tax burdens are solely for the first

[27] These baseline tax rates are similar to those purposed by Sevigny (1998).

year following imposition of the VMT tax. Household behavior and the population of drivers are likely to adjust over time and thus require adjustments in the VMT tax rate

Under the assumption of heterogeneous households, emissions decreases are 7% and 12%, respectively (with the same average annual tax burdens).[28] Thus, the heterogeneous-household model not only produces respectively lower estimates of $PM_{2.5}$ emissions, but also a tighter range between the high- and low-end estimates. These results are driven by (no pun intended) adjustments made for commuter-vehicle VMT elasticities in the one-, two, and three-vehicle households (see Table 6, This Study columns).[29]

Assuming that $PM_{2.5}$ emissions and concentrations correlate one-for-one (i.e., one gram of emissions equals one $\mu g/m^3$) and the estimated percentage emissions reductions occur on a daily basis, Figure 3 shows that our upper-bound estimate of a 23% reduction in $PM_{2.5}$ emissions would not (counterfactually) have reduced emissions enough during the past year to meet the new NAAQS of $35\mu g/m^3$ (although it would have met the older NAAQS of $65\mu g/m^3$.[30] This in turn suggests that either the tax rates assumed for this analysis are too low, or a VMT tax alone is unlikely to be sufficient in helping Cache County avoid reaching non-attainment status with the EPA in the future. Additional policy measures, such as vehicle emissions testing, expanded mass transit or alternative transportation options, and targeted subsidies to promote use of mass transit and

[28] The heterogeneous household model for this analysis distinguishes commuter and non-commuter vehicles according to household income levels, i.e., a commuter vehicle from a high-income household, commuter vehicle from a middle-income household, commuter vehicle from a lower-income household, non-commuter vehicle from a high income household, etc.

[29] In cases where a commuter-vehicle VMT elasticity estimate is positive, we set the estimate to zero in calculating the $PM_{2.5}$ emissions reductions presented in Table 7.

[30] The two assumptions are possibly grandiose. The former depends on *inter alia* daily weather and traffic flow conditions. To our knowledge, there are no formal studies addressing the link between emissions and concentration. The latter depends on daily driving habits of households. Understanding these habits would require more detailed survey information than is presently available.

alternative transportation will therefore be necessary. Fortunately, revenues from the VMT tax would be available to help fund these measures.

6. Summary and Conclusions

This paper has addressed two interrelated issues. First, we provide updated VMT elasticity estimates that are conditioned on whether a household uses its vehicles for commuting purposes. We find that VMT elasticities are generally inelastic for vehicles that are used primarily for commuting purposes, but elastic for non-commuting vehicles. We also find that VMT elasticity increases in magnitude as household income level decreases for two- and three-or-more vehicle households. Second, we use our elasticity estimates to assess the effectiveness of different VMT tax rates in reducing $PM_{2.5}$ emissions in a non-attainment area located in northern Utah. Our principle findings are that a VMT tax rate of \$0.003 per passenger car mile and \$0.01 per light-duty truck mile would reduce annual $PM_{2.5}$ emissions in our study area by between 7% and 11%. At tax rates of \$0.006 and \$0.02 per mile for passenger cars and light-duty trucks, respectively, annual $PM_{2.5}$ emissions would be reduced by between 12% and 23%.

Our results are constrained by data limitations, in particular by information at the household level that would enable VMT taxes to be adjusted for 'seasonality' and 'location' effects. Seasonality pertains to the fact that, in this paper's study area, $PM_{2.5}$ emissions pose a threat to public health primarily during the winter inversion season. Location pertains to the fact that not all of a typical household's annual VMT occurs strictly within the affected area. Therefore, to be efficient VMT taxes should be applied only during the winter inversion season and only to miles driven within a designated area.

This type of targeted application necessitates a better understanding of household driving behavior during a given year.

In addition, household-level information is needed to control for fixed effects that might help explain why households with more than one vehicle, and which use their secondary or tertiary vehicles primarily for commuting purposes, have such low VMT elasticities for these commuter vehicles (in the case of our study, positive VMT elasticities). Measures of commuting distance, availability of mass transit, the household's subjective assessment of the possibility of substituting away from using their personal vehicles for commuting would likely be adequate controls in this respect. Also, longitudinal data (preferably panel) would enable measurement of changes in driving behavior over time as a result of the implementation of a VMT tax.

Several policy questions are left unanswered in this paper. For instance, should VMT tax revenues be used to replace existing vehicle registration fees? One would think the answer is "no", since VMT taxes are collected on an annual basis, not per mile. Thus, if VMT taxes are used to replace existing registration fees, households are more likely to consider the taxes to effectively be an annual fee. Moreover, revenue would then be unavailable to fund additional policy measures that might be needed in order to avoid reaching non-attainment status with the EPA. This begs a second question: what to do with VMT tax revenue? Obviously, the revenue could be used to fund these additional policy measures, such as vehicle emissions testing, expanded mass transit or alternative transportation options, and targeted subsidies to promote use of mass transit and alternative transportation.

A final issue is how to adjust VMT taxes to account for idling in traffic, which is not an insignificant contributing factor to $PM_{2.5}$ concentrations in metropolitan areas. Similar to the issues of seasonality and location, idling is easier to account for using gas taxes. However, in concert with more detailed household-level surveys that account for seasonality and location, studies that similarly assess the amount of time vehicles spend idling in traffic could be used to adjust VMT upward based on estimated idling times.

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Figure 1. Map of the U.S. Mountain Census District of the 2001 RTECS.

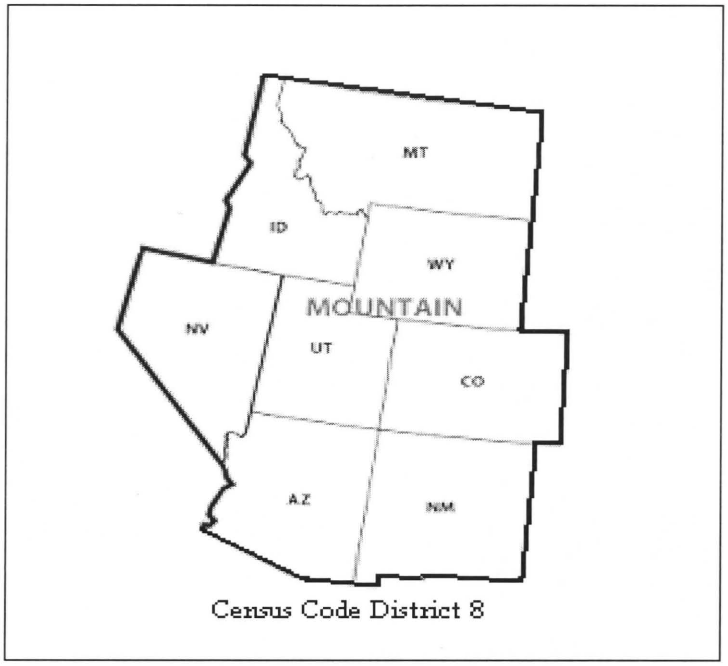
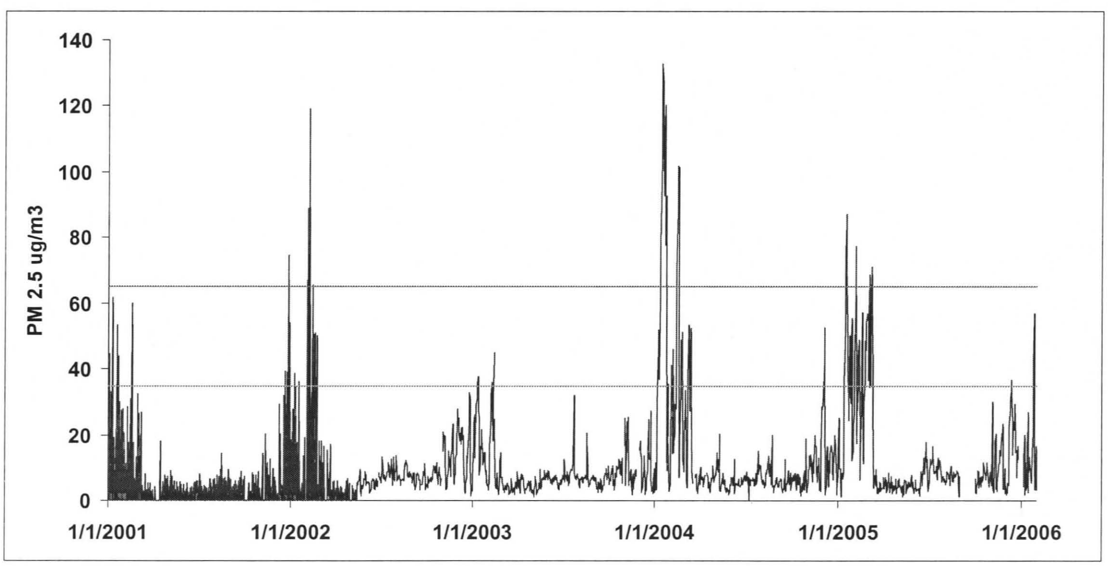


Figure 2. Cache County $PM_{2.5}$ Emission Levels 2001-2006.*



*Data from Utah Department of Environmental Quality.

Figure 3. Counterfactual Reduction in $PM_{2.5}$ Emission Levels for 2005.

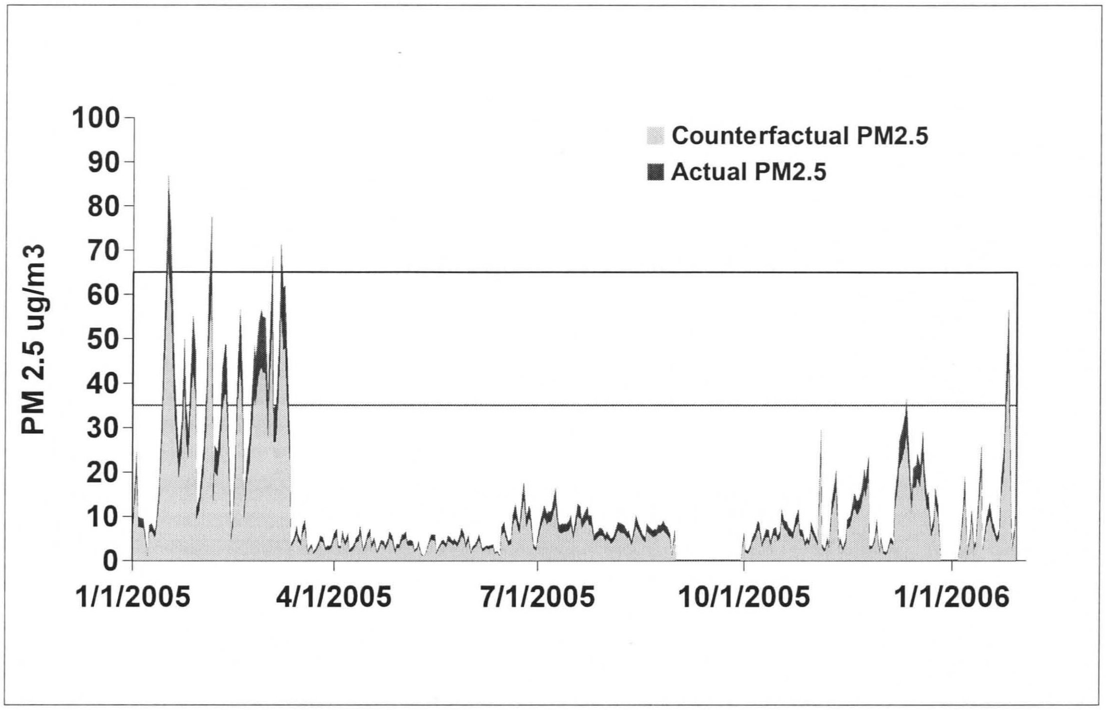


Table 1. Variable Descriptions and Descriptive Statistics (n = 1,585).

Variable Name	Mean	SD[a]	Description
vmt_1	12,168	11,319	VMT for household's first (i.e., primary) vehicle.
vmt_2	9,884	9,368	VMT for household's second (i.e., secondary) vehicle.
vmt_3	9,715	9,709	VMT for household's third (i.e., tertiary) vehicle.
vehgrt3	0.31	0.46	=1 if the household owns more than three vehicles, =0 otherwise.
numdrive	1.38	0.55	The household's number of registered drivers.
income[b]	38,477	24,094	Annual household income (in dollars).
lowinc	0.32	0.47	=1 if annual household income is less than $32,500.
midinc	0.50	0.50	=1 of annual household income is between $32,500 and $62,500.
gender	0.42	0.49	=1 if the head of household is male, =0 otherwise.
hhcomp	5.12	3.60	Household composition, indicating size, number of children, etc.
urban	0.87	0.32	=1 if household is located in an urban area, =0 otherwise.
$avecost_1$	0.07	0.02	Average fuel cost per mile for household's first vehicle.
$avecost_2$	0.08	0.03	Average fuel cost per mile for household's second vehicle.
$avecost_3$	0.09	0.05	Average fuel cost per mile for household's third vehicle.
cm_1	0.28	0.45	=1 if the first vehicle is a commuter vehicle, =0 otherwise.
cm_2	0.20	0.40	=1 if the second vehicle is a commuter vehicle, =0 otherwise.
cm_3	0.15	0.36	=1 if the third vehicle is a commuter vehicle, =0 otherwise.
$truck_1$	0.13	0.34	=1 if the first vehicle is a light-duty truck, =0 otherwise.
$truck_2$	0.30	0.46	=1 if the second vehicle is a light-duty truck,=0 otherwise.
$truck_3$	0.29	0.46	=1 if the third vehicle is a light-duty truck, =0 otherwise.

[a] SD = standard deviation.

[b] Our continuous measure of household income was constructed by taking the average of endpoints of the income intervals within which the households placed themselves. For example, the endpoints for interval1 are $0 and $4,999, implying a constructed income of $2,500; the endpoints for interval 2 are $5,000 to $9,999, implying a constructed income of $7,500; etc.

Table 2. Comparison of Mountain Sample and Cache County, Utah.

Variable Name	Sample Mean	County Mean
income ($)	38,477	39,730[a]
lowinc (%)	32	23
midinc (%)	50	55[b]
gender (%)	42	49
urban (%)	87	83[c]
$truck_i$ (%)	24[d]	33
one-vehicle households (%)	37	25
two-vehicle households (%)	40	42
three-or-more vehicle house. (%)	23	29[e]

[a]Median household income.

[b]Based on annual household income between $25,000 and $75,000.

[c]Based on population and authors' arbitrary distinction of urban.

dThe sample mean is a weighted average based on the sub-sample sizes for one-, two-, and three-or-more vehicle households.

[e]Percentages do not add to 100 because households with no vehicles are included in the census data.

Table 3. Estimation Results for One-Vehicle Households.[a,b]

Variables	OLS Estimates (3a)	OLS Estimates (3b)
constant	0.71**	0.32
	(0.288)	(0.365)
lincome	0.17***	0.13**
	(0.047)	(0.067)
$lavecost_1$	-1.85***	-2.34***
	(0.156)	(0.180)
numdrive	0.14***	0.12***
	(0.029)	(0.029)
hhcomp	-0.01***	-0.009**
	(0.004)	(0.004)
gender	0.07**	0.07***
	(0.029)	(0.029)
cm_1	0.48***	2.45***
	(0.036)	(0.369)
urban	-0.007	-0.005
	(0.045)	(0.044)
$truck_1$	-0.23	0.03
	(0.500)	(0.491)
$intert_1$	-0.38	-0.13
	(0.457)	(0.449)
$intercm_1$	---	1.68***
	---	(0.313)
interlinc	---	0.02
	---	(0.055)
interminc	---	0.03
	---	(0.043)
Sample Size	508	508
Adj. R-squared	0.57	0.59
F(9,498)	76.68***	---
F(12,495)	---	63.03***

[a]Dependent variable is $lvmt_1$.
[b]Standard errors in parentheses.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 4a. Estimation Results for Two-Vehicle Households – Equation (5a).[a]

Variables	OLS Estimates[b]	SUR Estimates[b]	OLS Estimates[c]	SUR Estimates[c]
constant	1.28***	-1.78***	1.74***	-2.64***
	(0.311)	(0.21)	(0.391)	(0.254)
lincome	0.14**	0.97***	0.08	1.10***
	(0.054)	(0.035)	(0.069)	(0.042)
$lavecost_1$	-1.63***	-1.33***	-0.09	-0.11
	(0.147)	(0.091)	(0.161)	(0.115)
$lavecost_2$	-0.05	0.36***	-1.32***	-0.99***
	(0.101)	(0.085)	(0.151)	(0.112)
numdrive	0.02	0.013	0.03	0.015
	(0.028)	(0.028)	(0.036)	(0.035)
hhcomp	-0.009**	-0.003	-0.01*	-0.004
	(0.005)	(0.005)	(0.006)	(0.006)
cm_1	0.42***	0.42***	---	---
	(0.033)	(0.032)	---	---
cm_2	---	---	0.51***	0.48***
	---	---	(0.046)	(0.045)
urban	-0.034	-0.07*	0.003	-0.04
	(0.037)	(0.037)	(0.047)	(0.046)
gender	-0.01	-0.06**	0.003	-0.05
	(0.029)	(0.028)	(0.036)	(0.035)
$truck_1$	0.20	-0.21	---	---
	(0.442)	(0.415)	---	---
$truck_2$	---	---	-0.89***	-1.05***
	---	---	(0.322)	(0.298)
$intert_1$	0.02	-0.34	---	---
	(0.408)	(0.385)	---	---
$intert_2$	---	---	-0.89***	-1.05***
	---	---	(0.298)	(0.276)
Sample Size	555	555	555	555
Adj. R-squared	0.43	---	0.41	---
F(10,544)	43.51***	---	39.62***	---
Chi-Square (10)	---	130.31***	---	125.24***
Wald Chi-Squ. (3)	---	433.93***	---	433.93***

[a]Standard errors in parentheses.
[b]Dependent variable is $lvmt_1$.
[c]Dependent variable is $lvmt_2$.
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 4b. Estimation Results for Two-Vehicle Households – Equation (5b).[a]

Variables	OLS Estimates[b]	SUR Estimates[b]	OLS Estimates[c]	SUR Estimates[c]
constant	0.76*	-2.54***	1.68***	-2.44***
	(0.454)	(0.310)	(0.565)	(0.372)
lincome	0.17**	1.04***	0.02	1.02***
	(0.089)	(0.050)	(0.112)	(0.060)
$lavecost_1$	-1.91***	-1.16***	-0.14	0.08
	(0.166)	(0.094)	(0.159)	(0.119)
$lavecost_2$	-0.08	0.12	-1.61***	-1.10***
	(0.100)	(0.088)	(0.164)	(0.114)
numdrive	0.02	0.04	0.03	0.04
	(0.028)	(0.028)	(0.036)	(0.035)
hhcomp	-0.008*	-0.005	-0.01**	-0.008
	(0.005)	(0.004)	(0.006)	(0.006)
cm_1	1.94***	1.44***	---	---
	(0.334)	(0.315)	---	---
cm_2	---	---	2.42***	2.19***
	---	---	(0.419)	(0.398)
urban	-0.027	-0.02	-0.001	0.001
	(0.037)	(0.037)	(0.046)	(0.046)
gender	-0.008	-0.04	0.01	-0.02
	(0.028)	(0.028)	(0.036)	(0.035)
$truck_1$	0.23	-0.32	---	---
	(0.436)	(0.411)	---	---
$truck_2$	---	---	-0.77**	-0.92***
	---	---	(0.318)	(0.296)
$intert_1$	0.07	-0.41	---	---
	(0.4025)	(0.411)	---	---
$intert_2$	---	---	-0.78***	-0.91***
	---	---	(0.295)	(0.275)
$intercm_1$	1.30***	0.85***	---	---
	(0.290)	(0.266)	---	---
$intercm_2$	---	---	1.64***	1.43***
	---	---	(0.357)	(0.338)
interlinc	-0.03	-0.28***	0.02	-0.28***
	(0.039)	(0.032)	(0.052)	(0.042)
interminc	-0.005	-0.21***	0.03	-0.19***
	(0.035)	(0.031)	(0.036)	(0.038)
Sample Size	555	555	555	555
Adj. R-squared	0.45	---	0.43	---
F(13,541)	36.22***	---	33.17***	---
Chi-Square (13)	---	263.21***	---	262.01***
Wald Chi-Squ. (3)	---	174.74***	---	174.74***

[a]Standard errors in parentheses. [b]Dependent variable is $lvmt_1$. [c]Dependent variable is $lvmt_2$.
***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

Table 5a. Estimation Results for Three-Vehicle Households – Equation (6a).[a]

Variables	OLS Estimates[b]	SUR Estimates[b]	OLS Estimates[c]	SUR Estimates[c]	OLS Estimates[d]	SUR Estimates[d]
constant	2.61***	-1.73***	1.88***	-2.98***	3.57***	-2.38***
	(0.364)	(0.275)	(0.430)	(0.343)	(0.538)	(0.428)
lincome	0.14**	1.01***	0.19**	1.20***	-0.10	1.07***
	(0.069)	(0.048)	(0.084)	(0.060)	(0.101)	(0.074)
$lavecost_1$	-0.73***	-1.03***	-0.12	-0.37***	0.14	-0.22
	(0.147)	(0.104)	(0.161)	(0.123)	(0.193)	(0.143)
$lavecost_2$	0.23*	0.21**	-0.92***	-0.91***	0.21	0.15
	(0.118)	(0.096)	(0.166)	(0.124)	(0.173)	(0.137)
$lavecost_3$	-0.14	-0.18**	0.10	0.08	-0.85***	-1.00***
	(0.095)	(0.085)	(0.116)	(0.105)	(0.151)	(0.134)
numdrive	-0.03	-0.07***	0.001	-0.05**	0.05	-0.004
	(0.021)	(0.020)	(0.026)	(0.025)	(0.032)	(0.030)
hhcomp	-0.017***	-0.01**	-0.01*	-0.005	-0.02***	-0.01*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.007)
cm_1	0.51***	0.44***	---	---	---	---
	(0.034)	(0.033)	---	---	---	---
cm_2	---	---	0.55***	0.59***	---	---
	---	---	(0.048)	(0.046)	---	---
cm_3	---	---	---	---	0.59***	0.49***
	---	---	---	---	(0.065)	(0.064)
urban	-0.01	-0.10***	-0.04	-0.14***	0.06	-0.04
	(0.037)	(0.036)	(0.045)	(0.043)	(0.053)	(0.052)
gender	0.02	-0.01	-0.003	-0.05	-0.02	-0.07
	(0.031)	(0.030)	(0.038)	(0.037)	(0.045)	(0.045)
vehgrt3	0.03	0.02	-0.02	-0.03	-0.02	-0.03
	(0.035)	(0.034)	(0.043)	(0.042)	(0.051)	(0.050)
$truck_1$	-0.82*	-0.66	---	---	---	---
	(0.485)	(0.460)	---	---	---	---
$truck_2$	---	---	-1.04**	-0.85**	---	---
	---	---	(0.450)	(0.420)	---	---
$truck_3$	---	---	---	---	-2.78***	-2.54***
	---	---	---	---	(0.395)	(0.383)
$intert_1$	-0.89*	-0.75*	---	---	---	---
	(0.454)	(0.432)	---	---	---	---
$intert_2$	---	---	-1.08**	-0.86**	---	---
	---	---	(0.424)	(0.398)	---	---
$intert_3$	---	---	---	---	-2.63***	-2.47***
	---	---	---	---	(0.377)	(0.365)
Sample Size	316	316	316	316	317	316
Adj. R-squared	0.55	---	0.44	---	0.50	---
F(12,304)	31.09***	---	21.64***	---	27.18***	---
Chi-Square (11)	---	125.15***	---	78.47***	---	118.97***
Wald Chi-Squ. (3)	---	459.72***	---	459.72***	---	459.72***

[a]Standard errors in parentheses.
[b]Dependent variable is $lvmt_1$. [c]Dependent variable is $lvmt_2$. [d]Dependent variable is $lvmt_3$.
[***]Significant at the 1% level. [**]Significant at the 5% level. [*]Significant at the 10% level.

Table 5b. Estimation Results for Three-Vehicle Households – Equation (6b).[a]

Variables	OLS Estimates[b]	SUR Estimates[b]	OLS Estimates[c]	SUR Estimates[c]	OLS Estimates[d]	SUR Estimates[d]
constant	2.90***	-2.25***	2.93***	-2.70***	3.54***	-2.98***
	(0.771)	(0.536)	(0.894)	(0.656)	(1.14)	(0.813)
lincome	0.01	1.05***	-0.08	1.11***	-0.13	1.11***
	(0.159)	(0.090)	(0.187)	(0.110)	(0.235)	(0.136)
$lavecost_1$	-1.04***	-1.04***	-0.14	-0.25*	0.13	-0.13
	(0.175)	(0.117)	(0.159)	(0.130)	(0.189)	(0.151)
$lavecost_2$	0.23*	0.17*	-1.13***	-0.91***	0.24	0.07
	(0.117)	(0.101)	(0.177)	(0.125)	(0.170)	(0.143)
$lavecost_3$	-0.13	-0.18**	0.09	0.05	-1.07***	-1.06***
	(0.094)	(0.087)	(0.115)	(0.105)	(0.160)	(0.137)
numdrive	-0.03	-0.03	-0.005	-0.005	0.04	0.04
	(0.021)	(0.020)	(0.026)	(0.024)	(0.031)	(0.029)
hhcomp	-0.02***	-0.017***	-0.01*	-0.01*	-0.02***	-0.02***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)
cm_1	1.50***	1.64***	---	---	---	---
	(0.326)	(0.298)	---	---	---	---
cm_2	---	---	2.07***	1.84***	---	---
	---	---	(0.551)	(0.517)	---	---
cm_3	---	---	---	---	2.53***	2.71***
	---	---	---	---	(0.485)	(0.469)
urban	-0.03	-0.05	-0.05	-0.07*	0.07	0.04
	(0.037)	(0.036)	(0.044)	(0.043)	(0.052)	(0.051)
gender	0.008	0.01	0.003	-0.001	-0.02	-0.02
	(0.031)	(0.030)	(0.038)	(0.037)	(0.045)	(0.044)
vehgrt3	0.04	0.02	-0.02	-0.03	-0.01	-0.02
	(0.035)	(0.034)	(0.042)	(0.041)	(0.050)	(0.049)
$truck_1$	-0.62	-0.50	---	---	---	---
	(0.483)	(0.456)	---	---	---	---
$truck_2$	---	---	-0.87*	-0.89**	---	---
	---	---	(0.444)	(0.415)	---	---
$truck_3$	---	---	---	---	-2.63***	-2.45***
	---	---	---	---	(0.389)	(0.376)
$intert_1$	-0.69	-0.59	---	---	---	---
	(0.453)	(0.427)	---	---	---	---
$intert_2$	---	---	-0.90**	-0.89**	---	---
	---	---	(0.419)	(0.392)	---	---
$intert_3$	---	---	---	---	-2.48***	-2.33***
	---	---	---	---	(0.371)	(0.358)
$intercm_1$	0.88***	1.00***	---	---	---	---
	(0.285)	(0.259)	---	---	---	---
$intercm_2$	---	---	1.33***	1.12***	---	---
	---	---	(0.478)	(0.447)	---	---
$intercm_3$	---	---	---	---	1.68***	1.83***
	---	---	---	---	(0.416)	(0.403)
interlinc	0.06	-0.57***	0.10	-0.62***	0.01	-0.80***
	(0.109)	(0.075)	(0.129)	(0.093)	(0.169)	(0.117)

interminc	0.065 (0.053)	-0.22*** (0.039)	0.15** (0.063)	-0.18*** (0.048)	0.03 (0.081)	-0.32*** (0.060)
Sample Size	317	316	316	316	317	316
Adj. R-squared	0.55	---	0.46	---	0.52	---
F(15,300)	26.32***	---	18.90***	---	23.82***	---
Chi-Square (15)	---	237.75***	---	186.02***	---	228.32***
Wald Chi-Squ. (3)	---	118.79***	---	118.79***	---	118.79***

[a] Standard errors in parentheses.
[b] Dependent variable is $lvmt_1$. [c] Dependent variable is $lvmt_2$. [d] Dependent variable is $lvmt_3$.
[***] Significant at the 1% level. [**] Significant at the 5% level. [*] Significant at the 10% level.

Table 6. Comparisons of VMT Elasticity Estimates Across Studies.

	Walls, et al. (1993)	Sevigny (1998)	West (2004)	This Study[a]		
			Vehicle			
	1st	1st	1st	1st	2nd	3rd
One-Vehicle Households						
passenger car[b]	-0.13	-0.85	-0.93	-1.85[c]	---	---
truck	---	---	---	-1.85[d]	---	---
commuter vehicle	---	---	---	-0.66	---	---
non-commuter vehicle	---	---	---	-2.34[e]	---	---
Two-Vehicle Households						
passenger car[b]	-0.52	-0.92	-0.93	-1.33[c]	-0.99	---
truck	---	---	---	-1.33[d]	-2.04	---
commuter vehicle	---	---	---	-0.31	0.33	---
non-commuter vehicle	---	---	---	-1.16[e]	-1.10	---
Three-Vehicle Households						
passenger car[b]	-0.92	-0.94	-0.93	-1.03	-0.91	-1.00
truck	---	---	---	-1.78	-1.76	-3.47
commuter vehicle	---	---	---	-0.04	0.21	0.77
non-commuter vehicle	---	---	---	-1.04	-0.91	-1.06

[a] Values for *passenger car* and *truck* are taken from Tables 3 (equation (3a)), 4a, and 5a. Values for *commuter* and *non-commuter vehicles* are taken from Tables 3 (equation (3b)), 4b, and 5b.
[b] Averaged over passenger cars and light-duty trucks for Walls, et al. (1993), Sevigny (1998), and West (2004). West (2004) does not distinguish VMT elasticity by household. Averaged solely over passenger cars from the homogeneous-household models (equations (3a), (5a), and (6a)) for this study.
[c−e] Statistically different at the 5% level of significance.

Table 7. Comparisons of $PM_{2.5}$ Emissions Reductions Under Alternative Tax Scenarios.

	Reduction in $PM_{2.5}$ Emissions (million kg.)[a]	Percent Reduction in $PM_{2.5}$ Emissions[a]	Average Annual Tax Burden ($/yr.)[b]
Tax Scenario 1			
Homogeneous Households	3.4	11	128
Heterogeneous Households	2	7	
Tax Scenario 2			
Homogeneous Households	6.7	23	256
Heterogeneous Households	3.5	12	

[a] The baseline condition is the current estimate of 29.6 million kg of $PM_{2.5}$ emissions per year with no VMT tax burden.

[b] Based on a 'two-stage' weighted average, where in the first stage a weighted average is calculated of the sum of the average VMTs for passenger cars and trucks – using the percentages of one-, two-, and three-vehicle households as the weights – and in the second stage a weighted average is calculated of the average VMTs for passenger cars and trucks – using the percentages of passenger cars and trucks as the weights.

Appendix 1

We begin by solving household i's problem, where E_{-i} is assumed exogenous. The problem may be expressed as $\underset{\{z_i, m_i\}}{MAX}\ U^i(z_i,\ \boldsymbol{m}_i\ E) + \lambda_i\{y_i - z_i - \boldsymbol{P}_j\boldsymbol{m}_i\}$, where λ_i represents household i's marginal utility of income. In solving this problem, we note that $E = \Sigma_j f^j(m_{ij}) + E_{-i}$, $i = 1,\ldots,n$ and $j = 1,\ldots,m$.

Optimality conditions for this problem are:

$$U_z^i = \lambda_i,\ i = 1,\ldots.,n \tag{A1}$$

$$U_{m_j}^i + U_E^i f_m^j \leq \lambda_i P_j,\ \ i = 1,\ldots.,n\ \ j = 1,\ldots.,m \tag{A2}$$

$$y_i = z_i + \ \boldsymbol{P}_j\boldsymbol{m}_i,\ \ i = 1,\ldots.,n \tag{A3}$$

where P_j is the j^{th} element of $\boldsymbol{P}_j$. Note that equations (A1) and (A2) represent standard equality conditions between marginal costs and benefits for goods z_i and m_j, respectively. Ratioing these two equations results in equations (1) in the text.

Solving now for the first-best VMT tax, we assume a benevolent social planner faces the problem $\underset{\{z_i, m_i\}}{MAX}\ \ \Sigma_i\,\alpha_i U^i(z_i,\ \boldsymbol{m}_i\ ,E) + \mu\{\Sigma_i(y_i - z_i - \boldsymbol{P}_j\boldsymbol{m}_i)\}$, where α_i are predetermined welfare weights, $\Sigma_i\,\alpha_i = 1$, and μ is the social marginal utility of income. Note that in this problem the social planner is constrained by an economy-wide budget constraint. The planner also endogenizes each vehicle's (of each household's) emissions, i.e. for the regulator $E = \Sigma_i \Sigma_j e_{ij}$, where each e_{ij} is effectively a choice variable.

The optimality conditions for this problem are:

$$\alpha_i U^i_z = \mu \text{ , } i = 1,\ldots\ldots,n \tag{A1'}$$

$$\alpha_i \; U^i_{m_j} \le \mu P_j \; - f^j_m \, \Sigma_i \, \alpha_i U^i_E \text{ , } i = 1,\ldots\ldots,n \;\; j = 1,\ldots\ldots,m \tag{A2'}$$

$$\Sigma_i (y_i - z_i - \boldsymbol{P_j} \, \boldsymbol{m_i}) = 0 \tag{A3'}$$

Equations (A1′) and (A2′) imply the Kuhn-Tucker conditions:

$$m_{ij} \left[\frac{U^i_{m_j}}{U^i_z} + \frac{f^j_m \, \Sigma_i \, \alpha_i U^i_E}{\alpha_i U^i_z} - P_j \right] = 0 \text{ , } i = 1,\ldots\ldots,n \;\; j = 1,\ldots\ldots,m \tag{A4}$$

Using (A1′), we note that (A4) may be re-written as:

$$m_{ij} \left[\frac{U^i_{m_j}}{U^i_z} + f^j_m \, \Sigma_i \left(\frac{U^i_E}{U^i_z} \right) - P_j \right] = 0 \tag{A4'}$$

which, *inter alia*, results in optimal $m_{ij}^* = m_{ij}^* \, (\boldsymbol{P_j}, \boldsymbol{\alpha}, \, y)$. Comparing (A4′) and (1) we observe that $\boldsymbol{m}_i > \boldsymbol{m}_i^* > 0$ for every vehicle type *j* driven by household *i*, given the optimal values of all other variables. In other words, all households *i* owning vehicle types *j* drive more miles than are optimal because they do not fully internalize the external effects of their VMTs on each other.

Finally, we return to household *i*'s problem to derive the set of first-best VMT tax rates. Household *i*'s problem is now $\underset{\{z_i, m_i\}}{MAX} \; U^i(z_i, \, \boldsymbol{m_i} \, , E) \; + \lambda_i \{y_i - Z_i - \, P_j m_i - \boldsymbol{t}_{ij} m_i\}$ where $\boldsymbol{t}_{ij} = \{t_{ij}\}_j$ in a vector of household- and vehicle-specific tax rates.

The first order conditions for this problem are:

$$U_z^i = \lambda_i \ , i = 1,....,n \tag{A1''}$$

$$U_{m_j}^i + U_E^i f_m^j \leq \lambda_i (P_j - t_{ij}) \leq 0 \, , i = 1,....,n \, , \ j = 1,....,m \tag{A2''}$$

$$y_i - z_i - \boldsymbol{m}_i (\boldsymbol{P}_j - \boldsymbol{t}_j) = 0 \, , i = 1,....,n \tag{A3''}$$

Equations (A1") and (A2") imply:

$$m_{ij} \left[\frac{U_{m_j}^i}{U_z^i} + \frac{f_m^j U_E^i}{U_z^i} - P_j - t_{ij} \right] = 0 \, , \ i = 1,....,n \, , \ j = 1,....,m \tag{A4'}$$

which implies, via comparison with (A4), the Pigovian tax rates $t_{ij}^* \equiv -f_m^j \sum_{-i} \left(\frac{U_E^{-i}}{U_z^{-i}} \right)$,

where the functions U_E^{-i}, f_m^j, and U_z^{-i} are each evaluated at corresponding z_i^*, $\boldsymbol{m}_i^*$, and e_{ij}^*. Hence, t_{ij}^* represents first-best VMT tax rate per household i and vehicle type j, $i = 1,....,n$ and $j = 1,...,m$.

Appendix 2

Table A2-1. Probit Estimation Results for $Truck_1$ in (3a).[a,b]

Variables	OLS Estimates
constant	-0.59
	(1.03)
lincome	0.03
	(0.236)
numdrive	0.06
	(0.144)
hhcomp	-0.07***
	(0.022)
cm_1	0.098
	(0.172)
urban	-0.63***
	(0.193)
gender	0.27*
	(0.144)
res_1	-0.03
	(0.2444)
Sample Size	508
Log-likelihood	-193.91
Chi-Square (7)	26.80***
McFadden R^2	0.06
Akaike I.C.	0.79
% 0s Correctly Pred.[c]	100
% 1s Correctly Pred.[c]	0

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 508 vehicles, 436 were non-trucks ($truck_1 = 0$) and 72 were trucks ($truck_1 = 1$).
***Significant at the 1% level.
*Significant at the 10% level.

Table A2-2. Probit Estimation Results for $Truck_1$ (Two-Vehicle Households).[a,b]

Variables	OLS Estimates
constant	-1.02
	(1.13)
lincome	0.06
	(0.238)
numdrive	0.11
	(0.121)
hhcomp	-0.01
	(0.020)
cm_1	0.10
	(0.137)
cm_2	0.21
	(0.148)
urban	-0.30**
	(0.152)
gender	0.007
	(0.123)
res_1	-0.004
	(0.194)
Sample Size	555
Log-likelihood	-288.71
Chi-Square (8)	9.71
McFadden R^2	0.02
Akaike I.C.	1.07
% 0s Correctly Pred.[c]	100
% 1s Correctly Pred.[c]	0

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 555 vehicles, 432 were non-trucks ($truck_1 = 0$) and 123 were trucks ($truck_1 = 1$).
**Significant at the 5% level.

Table A2-3. Probit Estimation Results for $Truck_2$ (Two-Vehicle Households).[a,b]

Variables	OLS Estimates
constant	1.62
	(1.05)
lincome	-0.38*
	(0.221)
numdrive	-0.04
	(0.118)
hhcomp	0.01
	(0.019)
cm_1	0.20
	(0.132)
cm_2	-0.11
	(0.150)
urban	-0.51***
	(0.144)
gender	0.03
	(0.118)
res_2	-0.01
	(0.137)
Sample Size	555
Log-likelihood	-322.61
Chi-Square (8)	21.46***
McFadden R^2	0.03
Akaike I.C.	1.20
% 0s Correctly Pred.[c]	96.46
% 1s Correctly Pred.[c]	4.38

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 555 vehicles, 395 were non-trucks ($truck_1 = 0$) and 160 were trucks ($truck_1 = 1$).
[***]Significant at the 1% level.
[*]Significant at the 10% level.

Table A2-4. Probit Estimation Results for $Truck_1$ (Three-Vehicle Households).[a,b]

Variables	OLS Estimates
constant	-1.21
	(1.58)
lincome	0.13
	(0.338)
numdrive	0.02
	(0.102)
hhcomp	0.02
	(0.026)
cm_1	-0.02
	(0.170)
cm_2	0.23
	(0.190)
urban	-0.35*
	(0.179)
gender	0.005
	(0.157)
vehgrt3	-0.004
	(0.177)
res_1	-0.03
	(0.302)
Sample Size	316
Log-likelihood	-175.80
Chi-Square (9)	5.99
McFadden R^2	0.02
Akaike I.C.	1.18
% 0s Correctly Pred.[c]	100
% 1s Correctly Pred.[c]	0

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 316 vehicles, 236 were non-trucks ($truck_1 = 0$) and 80 were trucks ($truck_1 = 1$).
[*]Significant at the 10% level.

Table A2-5. Probit Estimation Results for *$Truck_2$* (Three-Vehicle Households).[a,b]

Variables	OLS Estimates
constant	-0.84
	(1.61)
lincome	0.15
	(0.348)
numdrive	-0.02
	(0.102)
hhcomp	-0.009
	(0.026)
cm_1	0.23
	(0.166)
cm_2	-0.07
	(0.193)
cm_3	0.05
	(0.219)
urban	-0.42**
	(0.178)
gender	-0.23
	(0.158)
vehgrt3	0.04
	(0.177)
res_2	-0.007
	(0.243)
Sample Size	316
Log-likelihood	-179.30
Chi-Square (10)	11.36
McFadden R^2	0.03
Akaike I.C.	1.20
% 0s Correctly Pred.[c]	99.57
% 1s Correctly Pred.[c]	1.16

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 316 vehicles, 230 were non-trucks ($truck_1 = 0$) and 86 were trucks ($truck_1 = 1$).
[**]Significant at the 5% level.

Table A2-6. Probit Estimation Results for *Truck*$_3$ (Three-Vehicle Households).[a,b]

Variables	OLS Estimates
constant	3.69**
	(1.639)
lincome	-0.68*
	(0.350)
numdrive	-0.36***
	(0.110)
hhcomp	-0.02
	(0.026)
cm_1	-0.08
	(0.173)
cm_2	0.02
	(0.194)
cm_3	0.31
	(0.221)
urban	-0.31*
	(0.181)
gender	0.29*
	(0.157)
vehgrt3	-0.07
	0.180
res_3	0.005
	(0.199)
Sample Size	316
Log-likelihood	-177.46
Chi-Square (10)	28.04***
McFadden R^2	0.07
Akaike I.C.	1.19
% 0s Correctly Pred.[c]	94.62
% 1s Correctly Pred.[c]	9.68

[a]Standard errors in parentheses.
[b]Marginal effects are qualitatively similar to the coefficient estimates presented here (and are available upon request from the authors).
[c]Out of 316 vehicles, 223 were non-trucks ($truck_1 = 0$) and 93 were trucks ($truck_1 = 1$).
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.